Market Timing Ability and Mutual Funds:
A Heterogeneous Agent Approach

Bart Frijns[1]

Department of Finance, Auckland University of Technology

Aaron Gilbert

Department of Finance, Auckland University of Technology

Remco C.J. Zwinkels

Erasmus School of Economics, Erasmus University Rotterdam

November 2011

[1] Corresponding author. Private Bag 92006, 1142, Auckland, New Zealand. E: bfrijns@aut.ac.nz, T: +64 9 921 5706, F: +64 9 921 9940. Part of this paper is written while Zwinkels was visiting Auckland University of Technology, whose hospitality he gratefully acknowledges.

Market Timing Ability and Mutual Funds: A Heterogeneous Agent Approach

November 2011

Abstract

This paper proposes a novel approach to determine whether mutual funds time the market. The proposed approach builds on a heterogeneous agent model, where investors switch between cash and stocks depending on a certain switching rule. This represents a more flexible, intuitive, and parsimonious approach. The traditional market timing models are essentially a special case of our model with contemporaneous switching rule. Applying this model to a sample of 400 US equity mutual funds, we find that 41.5% of the funds in our sample have negative market timing skills and only 3.25% positive skills. 20% of funds apply a forward-looking approach in deciding on market timing, and 13.75% a backward looking approach. We also note that market timing differs considerably over fund styles.

Keywords: mutual funds, market timing, heterogeneous agents models

JEL – codes: G11, G23

1. Introduction

Given the number of mutual funds and the wealth invested with them, it is of little surprise that the performance and ability of mutual funds has been a source of considerable research. One strand of this research has focused on the market timing ability of fund managers. Market timing involves fund managers predicting the future direction of the market, and on the basis of that forecast adjusting the market exposure of the fund accordingly. Market timing ability is a justification for the existence of actively managed funds, as the fund manager's ability to time the market should provide extra returns that exceed the fees incurred from active management.

While market timing ability has received considerable attention, there is an ongoing debate on the correct approach to evaluate the market timing ability of fund managers; see, for example, Aragon and Ferson (2008) for a comprehensive overview of the literature on measuring portfolio performance. The best known approach was introduced by Treynor and Mazuy (1966) who argued that successful timers would increase exposure to the market when market returns are expected to be high and reduce exposure when market returns are expected to be low. This change in exposure would result in a convex relationship between fund and market risk premium, and can be captured by running a regression that includes a quadratic term for the market return. The idea of a convex relationship has been built on by a number of studies. However, significant concerns have been expressed about the use of return-based models. For example, Jagannathan and Korajcyzk (1986) argue that dynamic trading strategies may induce convexity even when no market timing exists. Furthermore, as certain stocks have option like features it is possible to find convexity in passive funds where no attempts at market timing are made. In addition, Goetzmann, Ingersoll and Ivkovich (2000) show that the timing ability of managers is biased downwards when timing is measured at a monthly frequency but engage in market timing on a daily basis. Different approaches have been employed to control for these biases.

Based on the return-based measures discussed above, two approaches have been employed to correct for the weaknesses in the models. Bollen and Busse (2001) and Busse (1999) use daily fund returns rather than the more commonly used monthly returns to study market timing. Using daily data, Bollen and Busse (2001) show a marked increase in evidence of market timing ability, both positive market timing and negative market timing (34% vs 11% for daily and monthly, respectively). Hence Bollen and Busse (2001) suggest that future studies need to focus on daily rather than monthly data. In another line of research, Chen and Knez (1996) and Ferson and Schadt (1996) argue that one of the problems has been the use of unconditional performance measures, and that conditioning on public information results in a more accurate evaluation of the ability of managers. Specifically, Ferson and Schadt (1996) show that after conditioning on public information much of the negative timing ability observed in funds disappears or becomes insignificant.[2]

In this paper, we introduce an alternative approach to time variation in market exposure by combining the market timing literature with the heterogeneous agent approach to switching. This novel approach takes into account both lines of research mentioned above. The heterogeneous agent literature in finance, as reviewed in Hommes (2006), describes how asset price dynamics can be explained by heterogeneous investors who apply time-varying investment strategies. Investors are heterogeneous in the sense that they have different types

[2]An alternate approach to the return-based measure has been employed by Jiang, Yao and Yu (2005). This study employs portfolio fund holding information to calculate a fund beta based on the weighted average of the betas of the individual stocks held. The timing measure is then calculated as the covariance between the fund beta and the return on the market. Jiang et al. (2005) show that this measure results in a reduction in funds with negative timing ability with most funds showing insignificant but positive timing ability.

of expectations concerning the future price of a risky asset, based on differences in interpretation of the available information. Typically, the agents, or investors, are assumed to either have a momentum expectation or a mean reversion expectation. Investors are then modelled to switch between different investment strategies based on the recent performance of these strategies (see Brock and Hommes, 1997, 1998). Hence, investors are assumed to apply a positive feedback strategy. The market price is subsequently assumed to be a time-varying weighted average of the two groups of agents. As a result, the behavior of the market as a whole is time-varying, providing an explanation for the momentum and mean reversion anomalies, excess volatility, volatility clustering, and excess kurtosis. A number of papers have illustrated the empirical validity of such an approach. Boswijk, Hommes, and Manzan (2006) estimte a heterogeneous agent model for the S&P500 and find significance of momentum and mean reversion, and switching between them. De Jong, Verschoor, and Zwinkels (2010) show similar results for the foreign exchange market, and Frijns, Lehnert, and Zwinkels (2010) for the options market.

Typically, the heterogeneous agent approach attempts to explain market dynamics by means of the time variying nature of expectations of investors. We generalize the heterogeneous agent approach by turning this relationship around; we explain the behavior of investors by studying the time-varying nature of their exposure to the market. We do this by allowing mutual funds to switch between the risk free rate and the market conditional on the expected excess market return. Whereas the heterogeneous agent literature has typically focused on describing market returns by modelling investor behavior, we take an opposite approach and attempt to explain mutual funds' returns by studying the time variation of their exposure to the market. This approach has some important advantages over the typical methods.

The market timing literature, as described above, has typically focused on deducing whether funds actually attempt to time the market and whether they are succesful at it. We take an important additional step by not only showing whether funds attempt to time the market, but also which information is used to take this decision. The multinomial switching function, as first proposed by Manski and McFadden (1981), represents a deterministic approach to time-varying coefficients. It is flexible enough to allow us to condition the time variation in market exposure of mutual funds on any information available, such as the set of public information as suggested by Ferson and Schadt (1996). In addition, it allows us to vary the investment horizon of investors. It is not unreasonable to assume that funds take a few days to decide before adjusting their market exposure. When conditioning switching exclusively on contemporaneous market returns, the model essentially reduces to the standard approach with squared market returns. Furthermore, our model is rather parsimonious as it only consumes one additional degree of freedom relative to the standard linear model, regardless of the amount of conditioning information added. This is especially in contrast to the conditional market-timing methods described in Aragon and Ferson (2008).

In the empirical application, we first show how the traditional market timing model is a special case of our more flexible, intuitive, and parsimonious switching model. Results reveal that there is indeed a large overlap between the model, but that our switching model is able to filter out more market timing behavior. The results indicate that 41.5% of the funds in our sample have negative market timing skills and only 3.25% positive. Subsequently, we present two examples of alternative conditioning variables that might be used to decide on switching. Our results show substantial cross-sectional variation in the behavior of mutual fund managers. Out of all 400 mutual funds in our sample, 20% of funds apply a forward-looking approach in deciding on market timing in that future returns are positively predictive for market exposure, and 13.75% apply a backward looking approach.

The remainder of the paper is organized as follows. Section 2 presents the empirical strategy to uncover the market timing skills of mutual fund managers. Section 3 discusses the data and Section 4 the results. Section 5 concludes.

2. Market Timing Strategies

To examine whether mutual fund managers apply market timing strategies and how, we propose the following model. In a market timing strategy, a fund manager increases or decreases the fund's exposure to the market depending on her/his expectation of the market's performance. We assume that, unconditionally, a fund will have a certain position in risk-free securities and risky assets, represented by the market, i.e.,

$$r_{it} = \alpha + (1-\overline{\delta}_i)\, r_{ft} + \overline{\delta}_i \beta_i r_{mt} + \varepsilon_{it}\,, \tag{1}$$

where r_{it} and r_{mt} are the raw returns of fund i and the market at time t, respectively, β_i measures the level of market risk of the mutual fund, and $\overline{\delta}_i$ measures the proportion of capital held in risky assets. Since proportions need to stay between a range of 0 and 1, we restrict $\overline{\delta}_i$ between zero and one.[3] Given the fact that mutual funds are typically restricted to

[3]As a consequence, Equation (1) cannot be estimated by ordinary least squares (OLS), but needs to be estimated by constrained maximum likelihood estimation (MLE), where these restrictions can be imposed. Alternatively, one could resort to constrained OLS estimation, also known as the Kuhn-Tucker Estimator (see e.g. Gourieroux et al., 1982). However, as our full model needs to be estimated by MLE, we also resort to this model for our benchmark.

long-only strategies, it comes natural that an increase in the exposure to the risky asset, i.e., an increase in $\bar{\delta}_i$, goes at the expense of exposure to the risk-free asset. This effect is unaccounted for in the typical market timing model. We estimate this model over the whole sample period, where we can consider the obtained coefficients as the unconditional market exposure. This serves as a benchmark when modeling conditional market exposure.

If the specific mutual fund follows an active market timing strategy, then we expect the proportion of capital allocated to risky securities to vary over time. Hence, in the conditional version of Equation (1), the fund manager will increase exposures to the market and to cash depending on her or his expectations of whether risk-free or risky assets will outperform,

$$r_{it} = \alpha + (1 - \delta_{it}) r_{ft} + \delta_{it} \beta_i r_{mt} + \varepsilon_{it}, \tag{2}$$

where δ_{it} is the time-varying proportion of money allocated to risky assets. This allocation is given by

$$\delta_{it} = w_{it} \bar{\delta}_i, \tag{3}$$

where w_{it} is the weight of risky assets and $\bar{\delta}_i$ is the unconditional allocation of money to risky assets.

Weights, w_{it}, are determined by a multinomial choice function (see Manski and McFadden, 1981) where switching occurs on the basis of expected relative profitability, i.e.

$$w_{it} = \frac{1}{1+\exp(\gamma(\pi_t^C - \pi_t^S))}, \tag{4}$$

where π_t^C and π_t^S are expected performance measures of cash and stocks, respectively. By construction, w_{it} is bounded between zero and one.

The sensitivity of fund managers to the difference in performance is given by γ, the so-called intensity of choice parameter. A positive (negative) γ implies that $w_{it,}$ increases (decreases) whenever the expected profitability of stocks increases relative to the expected profitability of cash. The absolute magnitude of γ measures the responsiveness of fund managers. With $\gamma = 0$, managers do not react to performance differences and is therefore passive when it comes to market timing. As γ increases (in absolute terms), fund managers become more aggressive in shifting capital between cash and stocks. In the extreme case where $|\gamma| \to \infty$, managers are either fully exposed to cash or fully exposed to the risky asset, conditional on infinitesimal small differences in expected performance. As such, $1/\gamma$ can be interpreted as a measure of status quo bias, as introduced in Kahneman, Slovic, and Tversky (1982). Status quo bias refers to the bias in human decision making which states that individuals have a tendency to hold on to the status quo. In our particular case, it refers to fund managers sticking to their unconditional risk exposure even though they expect one of the assets to perform better in the future.

The expected profitability measures π_t^C and π_t^S can have many functional forms and can include information from many sources, exogenous or endogenous, that (potentially) cause the fund manager to adjust the composition his portfolio. In this case, and in line with previous literature, we assume that the amount of capital allocated to stocks or kept in cash depends on the expected relative performance of stocks or cash. However, we acknowledge that fund managers do not want to deviate too much from their unconditional benchmark, and moderate the expected profits from additional holdings in either stocks or cash by the deviations from the unconditional holdings. We express the profit function in the following way,

$$\pi_{it}^{j} = \frac{S_{jt}}{\exp\left(\left|\delta_{it-1} - \bar{\delta}_i\right|\right)}, \tag{5}$$

where j stands for either cash or stocks, S_{jt} is the expected return of either holding cash or investing in risky assets, and π_{it}^{j} is the expected profitability measure for that particular strategy[4]. Hence, if a fund manager expects stocks (cash) to generate a higher return and the current exposure to stocks (cash) does not yet deviate too far from the unconditional exposure, she or he will increase the exposure to stocks (cash).

Given that a fund manager has an incentive to maximize assets under management, we assume that allocation occurs on the basis of expected returns.[5] A subsequent question is how expectations on future returns are formed. The approach is flexible enough to use any type of information, but here we test for three different configurations, representing three different degrees of complexity. The first setup uses contemporaneous returns, $S_{jt} = r_{jt}$; that is, the exposure to the market is a function of period t returns. This setup is essentially equivalent to the standard market timing methodology using the squared market return. The second setup assumes that portfolio managers act as positive feedback traders, $S_{jt} = r_{jt-1}$; i.e., expected

[4]We use the exponent in the denominator to ensure that we cannot divide by zero.
[5]Returns of the fund obviously cause assets under management directly, but also indirectly by attracting capital inflows; see Sirri and Tufano (1998).

returns are assumed to be a function of period *t - 1* returns. The final setup assumes perfect foresight $S_{jt} = r_{jt+1}$, where period *t+1* returns are inserted in the profit function (5).

To measure the presence of market timing conditional in any of the three configurations, we focus on the sign and significance of γ. A positive (negative) and significant value for γ would indicate that the fund managers perceives the conditioning information in π as a positive (negative) signal for future returns and adjusts exposure accordingly. Since both positive and negative market timing has been observed in the past, we have no expectations regarding the sign and size.

3. Data

We collect fund return data from TrimTabs Data Services. We collect this data on a daily basis, as suggested by Bollen and Busse (2001), from the earliest point available, 2 Feburary 1998 until 31 December 2004. Since we focus on market timing ability we remove any fund whose focus is not on US domestic equities. We further remove any balanced or hybrid funds and focus only on all equity funds for the US (we only include funds in the ICI categories 0 (aggressive growth), 1 (growth), 2 (growth and income), and 17 (equity income). This results in a sample of 400 mutual funds including live and dead funds. Both the risk free rate and the market return are extracted from K.R. French's Tuck MBA School of Business online data library. Table 1 presents the descriptive statistics of the mutual fund returns, risk free rate and market rate

INSERT TABLE 1 HERE

4. Results

4.1 Baseline results

We start by estimating a traditional model for market timing as a benchmark to investigate the presence of market timing (see Treynor and Mazuy, 1966), i.e.

$$r_{it} - r_{ft} = \alpha + \beta_1 (r_{mt} - r_{ft}) + \beta_2 (r_{mt} - r_{ft})^2 + \varepsilon_{it} . \tag{6}$$

The test for the presence of market timing centers on the sign and significance of β_2. If β_2 is positive and significant, this implies that fund managers increase their market exposure when the market is going up, therefore providing evidence for successful market timing.

INSERT TABLE 2 HERE

In Table 2, we report summary statistics for this regression. First, we note that α is on average negative at a value of 3.86% p.a., suggesting that the mutual funds in our sample, on average, underperform the market. Of the 400 funds we observe a significantly negative α for 89 funds, with only 16 producing significant positive α's. In terms of market risk (β_1), we find that, on average, funds track the market; the average β_1 is 0.969 and all β_1 are positive. There is, however, quite some variation in β_1, ranging from a minimum of 0.332 to a maximum of 1.750. When focusing on the market timing term β_2, we find that the average coefficient is negative. This suggests that, on average, there is negative market timing behavior; the exposure to the market is decreased when the market performs well. Looking at the percentiles of the distribution, we observe that β_2 is negative for most of the distribution. In 68 out of 400 cases we find that β_2 is significantly negative and thus significant evidence of fund manager timing the market the wrong way around. In only one case we find significant evidence of positive market timing. These finding are in line with previous literature that has also reported negative market timing ability. Studies such as Kon (1983), Chang and Lewellen (1984), Henriksson (1984) and Jagannathan and Korajczyk (1986) all find the majority of funds are unable to time, while those that can time are more likely to be perverse timers, as also suggested by Carhart (1997).

In Table 3, we report the results of our market timing model based on the switching driven by profit functions using contemporaneous returns. Broadly, these results are in line with the results presented in Table 2. Firstly, we observe that α's on average are negative with a value of 4.65% p.a.; a slightly larger underperformance than for the traditional market timing model. Second, when we look at $\bar{\delta}_i$, the unconditional proportion of capital invested in risky assets, we observe that, on average 93.1% of capital is allocated to risky assets. As a result, on average 6.9% of capital is kept in cash. There is some variation in this proportion, where the minimum investment is 50.8% and the maximum is, by definition, 100%. The results for the β's are the same as for the traditional market timing model. This suggests that what we capture with our market timing model is indeed very closely related to the traditional approach. When looking at the switching (market timing) coefficient γ, we find that it is, on average, negative. This implies that fund managers seem to switch away from the most profitable strategy, or stated differently, time the market the wrong way around. This is similar to the findings using the traditional switching approach. As with the traditional approach, we also find that the switching parameter is negative over most of the distribution of the funds. We further find that in 166 out of 401 cases there is evidence of negative switching and in 13 cases there is evidence for positive/correct market timing.[6] Hence, our market timing model based on switching reveals more evidence of active timing strategies than the traditional model, both positive and negative.

INSERT TABLE 3 HERE

To determine whether there is a relationship between the market timing implied by our model and the traditional market timing model, we present a scatter plot in Figure 1 where we plot the market timing coefficient of the traditional model β_2 on the x-axis versus the switching parameter γ on the y-axis.

The scatter plot reveals the close relationship between the two approaches, suggesting that this configuration of our model indeed captures a similar type of behavior as the traditional market timing model. An interesting observation is the somewhat concave shape of the relationship; in the lower left quadrant the values for γ are clearly lower than would be the case for a linear relationship. This is explained by the nonlinear functional form of the switching function (4); the marginal effect of a change in γ decreases as γ gets larger (in absolute sense).

INSERT FIGURE 1 HERE

As an alternative check we compute correlations between traditional and switching-based market timing and report these in Table 4. We observe that the correlation between the two

[6]We cannot conduct simple t-test on this coefficient, as 1. we obtain parameter from a constrained MLE and 2. standard t-test often turn out insignificant in these models as the switching parameter γ enters the model nonlinearly. We therefore perform a Likelihood Ratio (LR) test with two degrees of freedom that compares the performance of Equation (2) (the model with timing) with the performance of Equation (1) (the model without timing). A significant increase in model fit suggests significant evidence of market timing.

coefficients, β_2 and γ, is very strong at almost 0.93. Secondly, we also look at the significance of switching implied by the traditional model and our approach. Again, the correlation between these two is very strong at a value of 0.75.

4.2 Close-up: Morgan Stanley's Utilities B

To study the similarities and differences between the traditional market timing approach and our switching approach, we take a closer look at one fund, namely Morgan Stanley's Utilities B, which is an equity income fund. We have chosen this particular fund because it yields significant results for both the market timing and the switching models; otherwise it is a random choice.

Table 5 displays the descriptive statistics of the time series of total market exposures for the market timing and switching models. For the former, total market exposure is given by $\beta_1 + 2\beta_2 r_{mt}$ and for the latter by $w_{i,t}\bar{\delta}_i\beta_i$. In terms of mean and median, the two are very similar. The correlation between the two measures is close to one. The market timing approach, though, yields a far more volatile market exposure given the double standard deviation and minimum – maximum range. This suggests that the traditional approach implies more aggressive switching between cash and stocks.

INSERT TABLE 5 HERE

Figure 2 illustrates a number of characteristics of the time-varying market exposures. The top two figures display the time series of total market exposure for the two models. The two series show a similar pattern, with high volatility in the first part of the sample, and lower volatility in the second part. The average exposure is comparable. Again, it becomes apparent that the market timing model yields more volatile exposures, i.e. more aggressive switching, than the heterogeneous agents model.

The bottom left plot shows the sensitivity of the two models to excess returns. The line for the switching model is somewhat less noisy than the other. This is caused by the fact that market timing in the switching model is based on excess returns, while it is based on absolute returns in the traditional market timing model. For both models, the estimation results pointed towards negative switching; i.e., market exposure is lower when excess returns are higher. This is clearly illustrated in the bottom left panel. The switching model is less sensitive to excess returns given the somewhat flatter line.

The bottom right panel, finally, illustrates the close relation between our switching model and the traditional approach. The scatter plot of the market exposures yields a straight line. The range on the vertical axis, though, is smaller than the range on the horizontal axis.

4.3 Forward Looking and Backward Looking Timing

The results using the contemporaneous returns as expected returns in the profit function in Table 3 have shown that the traditional approach to market timing is essentially a special case of our heterogeneous agents-inspired switching mechanism. To illustrate the flexibility of the model, we subsequently study whether mutual funds managers apply forward or backward looking expectations in deciding on whether to change their fund's exposure to the risky asset. To be more specific, we run the switching model using lagged and lead returns as decision variables in the profit functions π_{it}^{j}. As indicated before, the model is flexible enough to include any decision variable. Here, though, we choose to examine lead and lagged returns as there is a clear economic intuition behind these variables. Expectations based on lagged returns signal adaptive expectations while lead returns signal rational expectations. The estimation results are given in Table 6.

INSERT TABLE 6 HERE

Table 6 presents the cross-sectional distribution of the switching parameter γ obtained from the model using lagged and lead returns in the profit functions. Regarding the lagged returns; while the average γ was negative using the contemporaneous returns as decision variable, the average γ is positive when using the backward looking returns. In other words, on average mutual funds increase their exposure to the market when previous day's return are positive and when next day's return are positive. In 55 cases, we find a significantly positive γ for the timing lag; hence, 55 funds significantly increase their exposure to the market in period t after a positive market premium in period $t-1$, such that they behave like positive feedback traders. 45 funds are negative feedback traders, that is, they decrease their exposure to the market following positive excess market returns. Apparently, these fund managers believe in mean reversion and apply a contrarian strategy.

Concerning the timing lead, the average γ is again positive. We find that 80 funds significantly increase their exposure to the market in anticipation of positive excess market returns; they therefore appear to have perfect foresight. This may suggest that there are fund manager that do time the market in a correct way, but do not do this contemporaneously as tested in many studies before, but by increasing their market exposure on the day prior to positive market returns. This could be a result of the daily frequency; adjusting exposure on a daily basis might be too costly. Interestingly, 41 funds behave exactly opposite and decrease their exposure in reaction to a positive future return. It is hard to rationalize how this can be a deliberate strategy.

4.4 Behavior across Fund Types

As a final test, we study whether we observe differences in market timing for different styles of funds. Here, we split the sample of 400 domestic equity funds into the three ICI classifications aggressive growth (0), growth (1), growth and income (2), and equity income (17). Table 7 shows the results.

INSERT TABLE 7 HERE

Focusing on the traditional market timing model first, we observe that the aggressive growth funds are the most active in trying to time the market; over 25% of the funds. Note, however, that they all time negatively. The growth funds are clearly the least active (10%) and the growth and income and equity income funds are comparable with 16% and 13%.

Results for the switching model, spread over the three forecasting rules, gives a more detailed image of the behavior. As for the overall results, we observe more significant timing when applying our switching model for all styles. Clearly, though, the funds in the different classes do not behave similarly. The equity income funds are most actively in switching based on time t returns; 60% of the funds use that strategy, but all negatively. The least active group is again the growth funds, with 37%. Interestingly, the group of growth funds is the most active in switching based on lagged returns; in other words, the growth funds show the most evidence of feedback trading. For both the growth & income funds and the equity income funds we find a proportion of 31% that uses a forward looking strategy. Overall, we find that close to 50% of the funds in the sample apply a market-timing strategy based on our switching model. This percentage is equally split in forward looking funds and backward looking funds.

5. Conclusion

In this paper we propose a new approach to measure the market timing ability of mutual fund managers. The proposed approach builds on the heterogeneous agent literature, in which agents are allowed to switch between certain trading rules. The switching between these rules is driven by the relative performance of the different strategies. In this case, we assume that fund managers can switch between holding cash and stocks, depending on which asset type they think will outperform the market. Compared with the traditional market timing approach of Treynor and Mazuy (1966), our model is more flexible, in the sense that switching can be driven by many or even multiple factors. Furthermore, it gives a richer economic interpretation and is more parsimonious than, for example, the conditional market timing models.

We empirically implement our model to a sample of 400 US equity mutual funds, and use different rules for the switching between cash and stocks; a contemporaneous switching rule, which is equivalent to the traditional model of Treynor and Mazuy (1966); a forward-looking rule (assuming perfect foresight of fund managers); and a backward-looking used to examine whether fund managers behave as feedback traders. We find that 41.5% of the funds in our sample have negative market timing skills and only 3.25% positive skills. 20% of funds apply a forward-looking approach in deciding on market timing, and 13.75% a backward looking approach. We also note that market timing activity and ability differs considerably over fund styles.

References

Aragon and Ferson (2008). Portfolio performance evaluation, *Foundations and Trends in Finance* 2: 83 – 190.

Bollen, N. and Busse, J. (2001). On the Timing Ability of Mutual Fund Managers. *Journal of Finance, 56,* 1075-1094.

Boswijk, H. P., C. H. Hommes and S. Manzan (2007). Behavioral Heterogeneity in Stock Prices, *Journal of Economic Dynamics and Control* 31(6): 1938-1970.

Brock, W. and C. H. Hommes (1997). A Rational Route to Randomness, *Econometrica* 65(5): 1059-1095.

Brock, W. and C. H. Hommes (1998). Heterogeneous Beliefs and Routes to Chaos in a Simple Asset Pricing Model, *Journal of Economic Dynamics and Control* 22(8-9): 1235-1274.

Busse, J. (1999). Volatility Timing in Mutual Funds: Evidence from Daily Returns. *Review of Financial Studies, 12,* 1009-1041.

Chang, E. and Lewellen, W. (1984). Market Timing and Mutual Fund Investment Performance. *Journal of Business, 57,* 57-72.

Chen, Z. and Knez, P. (1994). Mutual Fund Performance: A nonparametric empirical investigation. *Review of Financial Studies, 9*, 511-555.

De Jong, E., W. F. C. Verschoor, and R. C. J. Zwinkels (2010). Heterogeneity of Agents and Exchange Rate Dynamics: Evidence from the EMS, *Journal of International Money and Finance*, 29(8): 1652-1669.

Elton, E., Gruber, M., Das, S. and Hlavka, M. (1992). Efficiency with Costly Information: A reinterpretation of evidence for managed portfolios. *Review of Financial Studies, 6,* 1-22.

Ferson, W. and Schadt, R. (1996). Measuring Fund Strategy and Performance in Changing Economic Conditions. *Journal of Finance, 51,* 425-461.

Frijns, B., T. Lehnert, and R.C.J. Zwinkels (2010). Behavioral Heterogeneity in the Option Market, *Journal of Economic Dynamics and Control*, forthcoming.

Goetzmann, W., Ingersoll, J. and Ivkovich, Z. (2000). Monthly Measurement of Daily Timers. *Journal of Financial and Quantitative Analysis, 35,* 257-290.

Gouriéroux, C., Holly A., and A. Montfort (1982). Likelihood Ratio Test, Wald Test and Kuhn-Tucker Test in Linear Models with Inequality Constraints on the Regression Parameters, *Econometrica* 50, 63-80

Henriksson, R. (1984). Market Timing and Mutual Fund Performance: An empirical investigation. *Journal of Business, 57,* 73-96.

Hommes, C. (2006). Heterogeneous Agent Models in Economics and Finance. In: Tesfatsion, L. and Judd, K.L. (Eds.), *Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics*, Elsevier Science B.V.

Jagannathan, R. and Korajczyk, R. (1986). Assessing the Market Timing Performance of Managed Portfolios. *Journal of Business, 59,* 217-235.

Jiang, G., Yao, T. and Yu, T. (2007). Do Mutual Funds Time the Market? Evidence from Portfolio Holdings. *Journal of Financial Economics, 86,* 724-758.

Kahneman, D., P. Slovic, and A. Tversky (1982). *Judgment under Uncertainty: Heuristics and Biases*, Cambridge University Press, Cambridge.

Kon, S. (1983). The Market Timing Performance of Mutual Fund Managers. *Journal of Business, 50*, 323-348.

Manski, C.F. and D. McFadden (1981). Alternative Estimators and Sample Designs for Discrete Choice Analysis, in: C.F. Manski and D. McFadden (eds.), *Structural Analysis of Discrete Data with Economic Applications*, MIT Press: Cambridge.

Sirri, E. and P. Tufano. (1998). Costly search and mutual fund flows. *Journal of Finance, 53*, 1589-1622.

Treynor, J. and Mazuy, K. (1966). Can Mutual Funds Outguess the Market? *Harvard Business Review*, *44,* 131-136.

Tables and Figures

Table 1 Descriptive Statistics

	#obs	mean	stdev	min	max	skew	kurt
Percentiles							
1%	92	-0.0943	0.3991	-67.9893	1.05774	-17.8984	-0.2252
5%	221	-0.0413	0.6396	-32.8572	1.9415	-5.0290	-0.0766
25%	605	-0.0124	1.0602	-15.5723	4.5704	-1.1575	1.1012
50%	983	0.0042	1.2530	-7.7363	5.6318	-0.2025	3.2370
75%	1733	0.0278	1.5123	-4.1772	7.4668	0.0509	18.0077
95%	1733	0.0925	2.0427	-2.0160	18.2732	0.2915	115.2984
99%	1733	0.1106	2.6988	-1.5865	25.8158	0.5819	467.4528
RF	1733	0.0001	0.0001	0.0000	0.0002	0.0841	-1.6283
RM	1733	0.0264	1.2487	-6.6260	5.3170	0.0157	2.1005

Notes: Table 1 presents descriptive statistics of the returns of the 400 mutual funds in our sample, the risk free rate RF and the market return RM. The percentiles represent the cross-section of funds.

Table 2 Traditional Market Timing

	α	β_1	β_2
Mean	-3.86%	0.969	-0.861
Standard Dev	8.47%	0.240	1.269
Min	-55.54%	0.332	-5.165
Max	16.80%	1.750	2.620
Skewness	-0.591	0.070	-0.489
Kurtosis	6.752	2.836	4.011
Significant +	16	400	1
Significant -	89	0	68
Percentiles			
5%	-16.25%	0.576	-3.359
25%	-8.93%	0.797	-1.478
50%	-4.47%	0.959	-0.746
75%	1.21%	1.135	-0.085
95%	10.13%	1.344	1.147

Notes: Table 2 presents the distributional statistics of the estimated coefficients of the traditional market timing model given by Equation (6). ‘Significant +’ and ‘Significant –‘ represent the number of significantly positive and negative coefficients out of a total of 400.

Table 3 Switching Model

	α	$\bar{\delta}$	β	γ
Mean	-4.65%	0.931	0.969	-3.261
Standard Dev	8.73%	0.124	0.240	4.529
Min	-56.12%	0.508	0.332	-28.385
Max	18.01%	1.000	1.750	6.823
Skewness	-0.519	-1.756	0.068	-1.207
Kurtosis	6.209	4.915	2.842	6.392
LR +				13
LR-				166
Percentiles				
5%	-17.58%	0.639	0.576	-10.872
25%	-9.89%	0.909	0.799	-5.389
50%	-5.02%	1.000	0.961	-2.790
75%	0.80%	1.000	1.132	-0.277
95%	10.29%	1.000	1.344	3.011

Notes: Table 3 presents the distributional statistics of the switching model with contemporaneous returns given by Equations (2) – (5). 'LR +' and 'LR –' represent the number of funds out of 400 for which we find a significantly positive and significantly negative value for γ.

Table 4 Correlations

	Switching		LR Switch
Market Timing	0.926	T-Market Timing	0.752

Notes: Table 4 presents the correlation between the market timing coefficients β_2 and γ (left hand side) and the correlation between the significance of these coefficients (right hand side).

Table 5 Conditional Market Exposures

	Market timing	Switching
Mean	0.6882	0.6889
Median	0.6857	0.6877
Maximum	0.9810	0.8279
Minimum	0.2871	0.4952
Std. Dev.	0.0873	0.0418
Skewness	-0.2974	-0.2700
Kurtosis	4.8860	4.8217
Market timing	1.0000	
Switching	0.9995	1.0000

Notes: Table 5 presents the descriptive statistics of the conditional market exposures of the traditional market timing model and out switching model. The former is given by $\beta_1+2\,\beta_2 R_m$ and the latter is given by $w_{it}\,\overline{\delta}\beta_i$.

Table 6 Forward and Backward Looking

		Timing Lag	Timing Lead
Mean		1.196	1.421
Standard Dev		5.978	6.649
Min		-23.125	-37.469
Max		26.886	45.062
Skewness		0.771	0.894
Kurtosis		6.256	12.925
LR +		55	80
LR-		45	41
Percentiles			
	5%	-6.849	-6.801
	25%	-2.265	-1.877
	50%	0.297	0.410
	75%	3.759	4.674
	95%	11.799	11.087

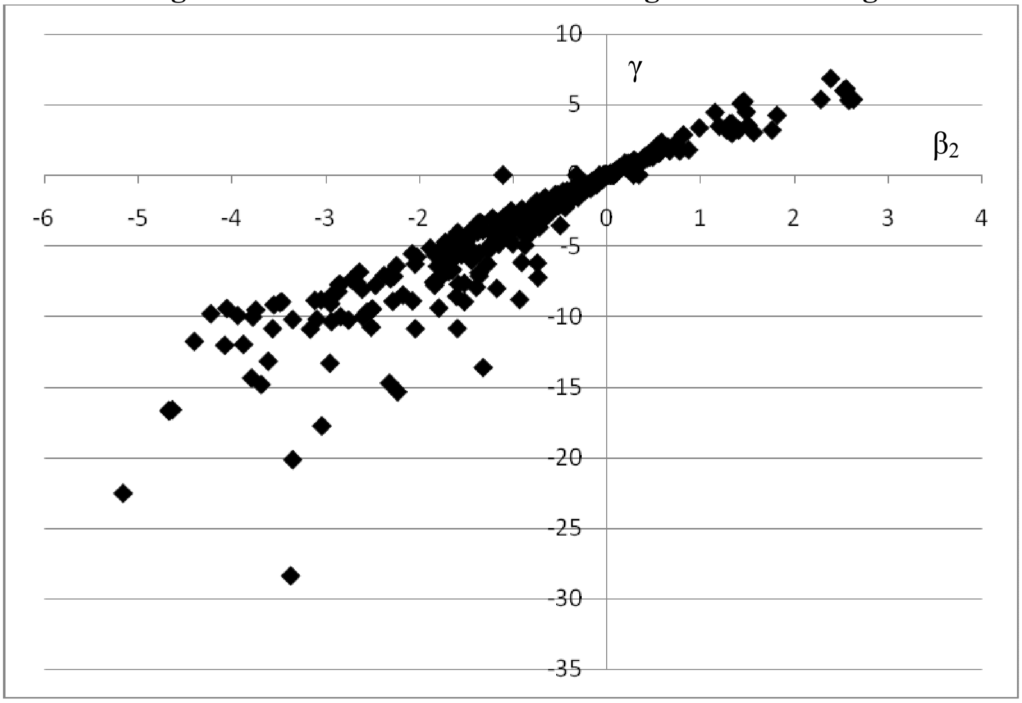
Notes: Table 6 presents the distributional statistics of the switching parameter γ for the case of backward looking expectations (Timing Lag) and forward looking expectations (Timing Lead). 'LR +' and 'LR –' represent the number of funds out of 400 for which we find a positive or negative significant γ.

Table 7 Investment Styles

	Numbers				Percentages			
	Traditional	Switching			Traditional	Switching		
	Timing	Cont.	Lag	Lead	Timing	Cont.	Lag	Lead
Aggressive Growth (0)								
+	0	5	19	20	0.00%	3.60%	13.67%	14.39%
-	35	71	13	21	25.18%	51.08%	9.35%	15.11%
Growth (1)								
+	1	9	24	22	0.72%	6.52%	17.39%	15.94%
-	13	43	27	19	9.42%	31.16%	19.57%	13.77%
Growth & Income (2)								
+	0	0	12	31	0.00%	0.00%	11.88%	30.69%
-	17	42	8	5	16.83%	41.58%	7.92%	4.95%
Equity Income (17)								
+	0	0	2	7	0.00%	0.00%	9.09%	31.82%
-	3	13	1	0	13.64%	59.09%	4.55%	0.00%
TOTAL								
+	1	14	57	80	0.25%	3.50%	14.25%	20.00%
-	68	169	49	45	17.00%	42.25%	12.25%	11.25%

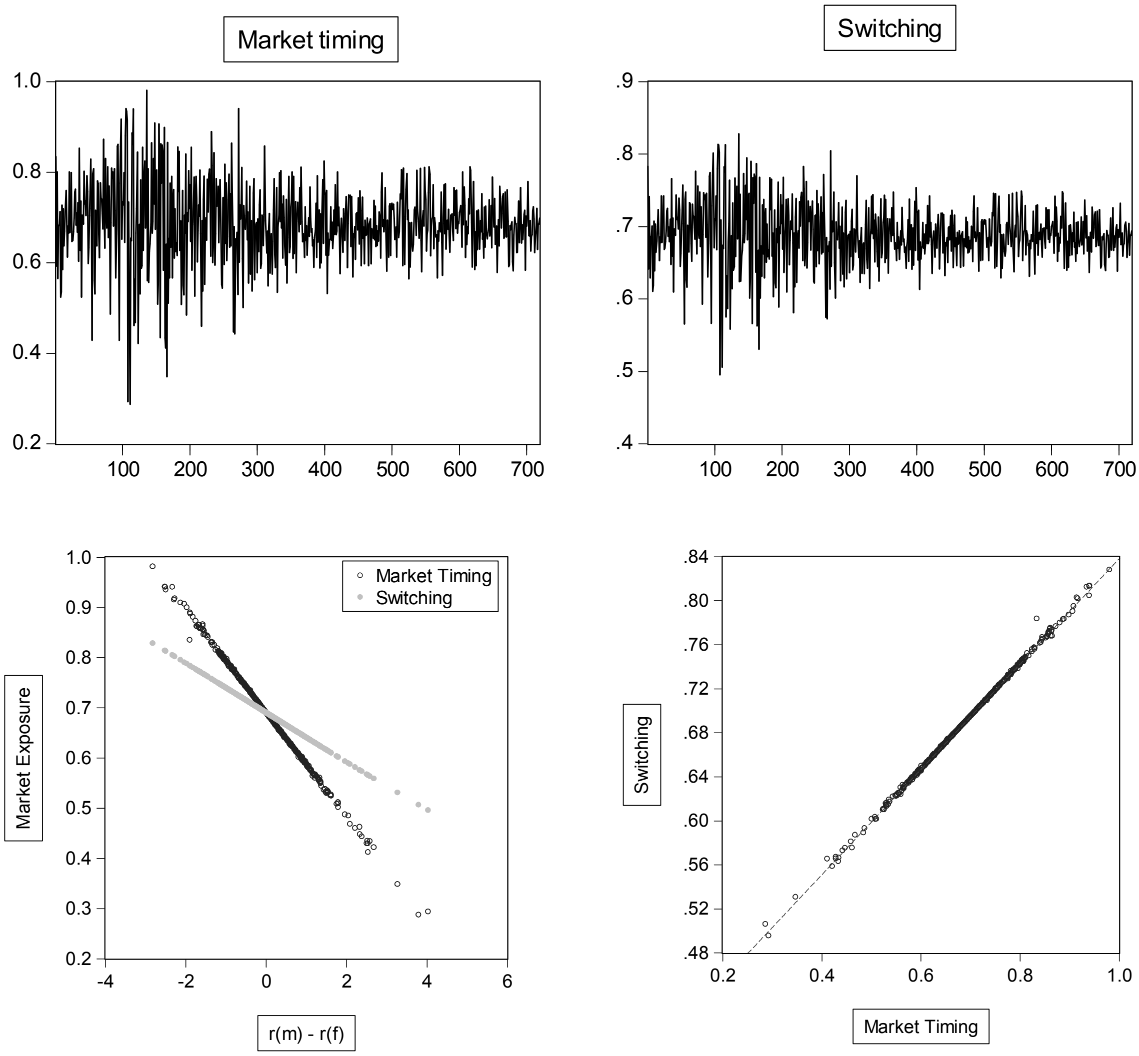
Notes: Table 7 presents the number of funds for which we find significant results over all specifications of the model split out over the four different investment styles.

Figure 1 Traditional versus Switching Market Timing



Notes: Figure 1 presents a scatter plot of the 400 estimated β_2 from the traditional market timing model (horizontal axis) and γ from the switcing model (vertical axis).

Figure 2 Conditional Exposures



Notes: Figure 2 compares the conditional market exposure implied from the traditional market timing model with that of the switching model. The upper two plots represent time-series of the conditional exposures. The lower-left plot gives the relation between the excess market return (horizontal axis) and the conditional market exposure (vertical axis). The lower right plot gives the relation between the conditional exposure of the market timing model (horizontal axis) and the switching model (vertical axis).